DEEP ENCODED LINGUISTIC AND ACOUSTIC CUES FOR ATTENTION BASED END TO END SPEECH EMOTION RECOGNITION

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Introduction

- Speech Emotion Recognition (SER) has several applications
  - man-machine interactions
  - human health assistance
  - call center analytics etc.

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  have significantly impacted SER.

- Can be further improved by exploiting,
  - ➢ Acoustic information : Spectrograms from raw audio and glottal source signals
  - ➢ Linguistic information : Text, Phoneme sequences, intermediate DNN representations

Related Work

Two directions :

- Use complex hand-crafted features (ex: OpenSMILE feature set)
- Deep modelling with conventional raw audio spectrograms

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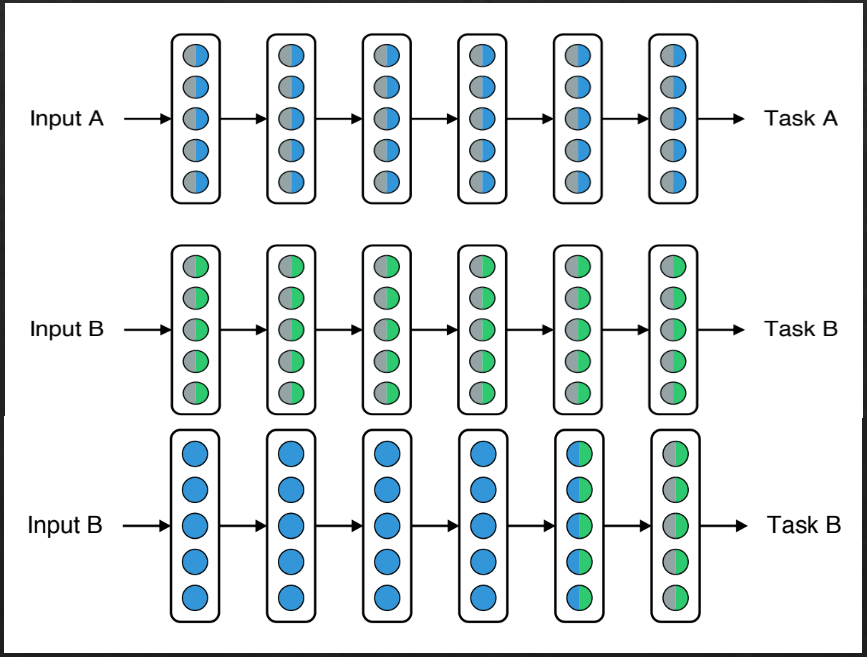
- In Deep networks,
  - initial layers ➔ low-level features
  - final layers ➔ high-level features
- Transfer learning ➔ share knowledge across datasets and tasks.



[1] https:/ /haythamfayek.com/assets/talks/Fayek_neurips18.pdf

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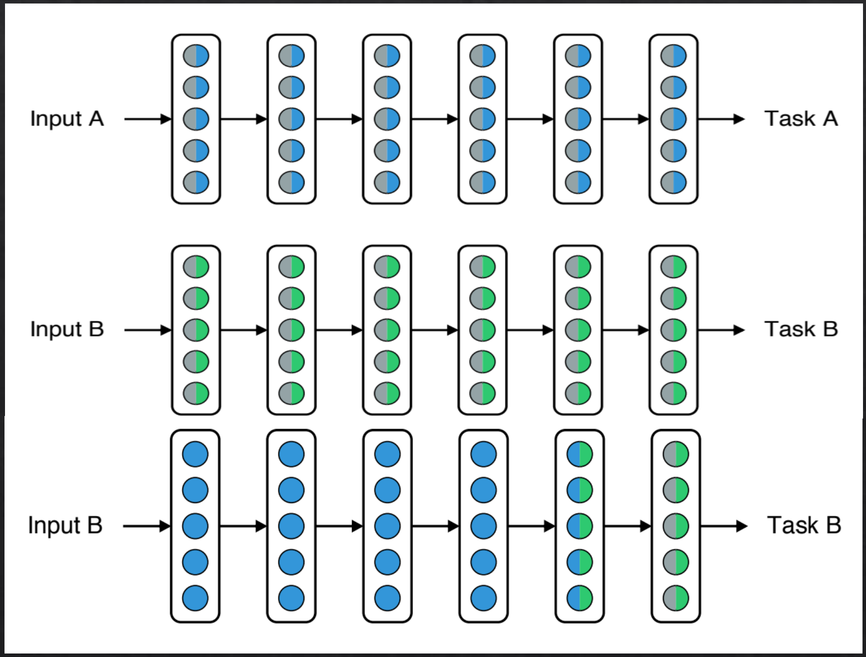

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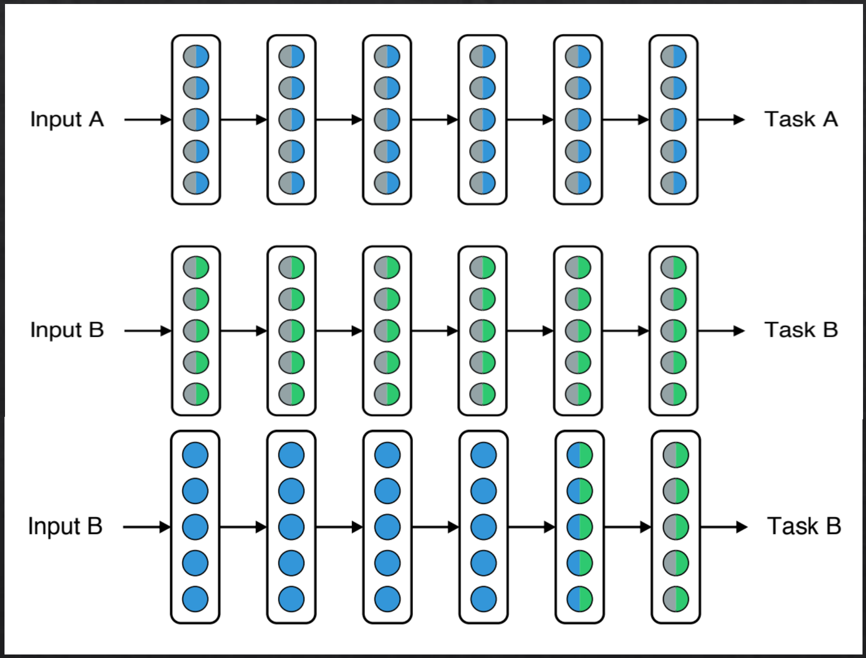
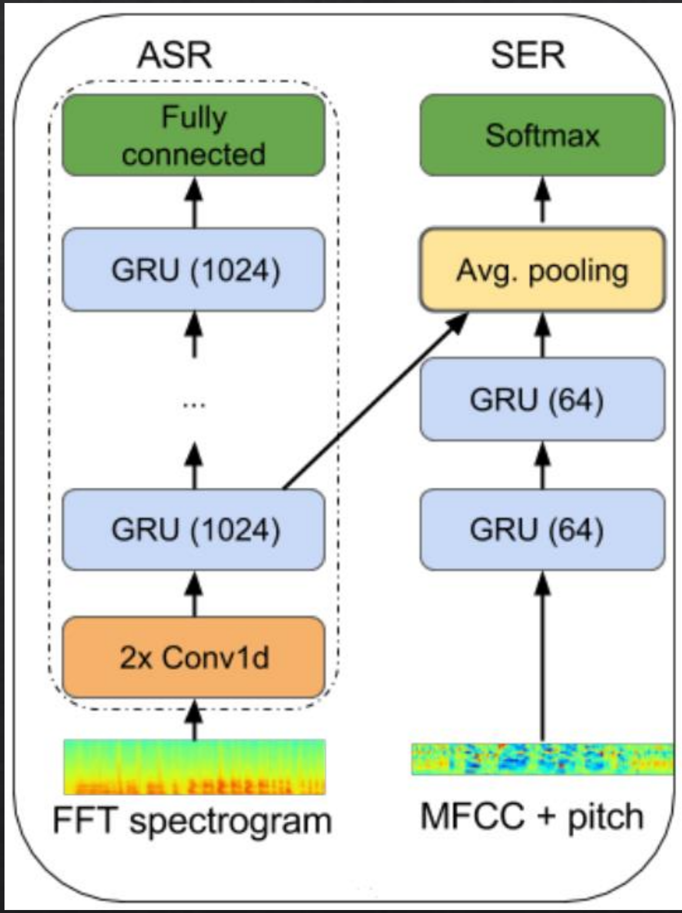


"Low-level features are more generic and easier to transfer from one task to another"
Could there be exceptions?

Related Work

Jointly learning supplementary tasks [2]

- Uncertainty about most relevant and robust features/layers
- Progressive network : training ASR and SER tasks jointly
- ASR representations show improved performance mainly due to the robustness to speaker and condition variations.



[2] https://www.aclweb.org/anthology/I17-1043.pdf

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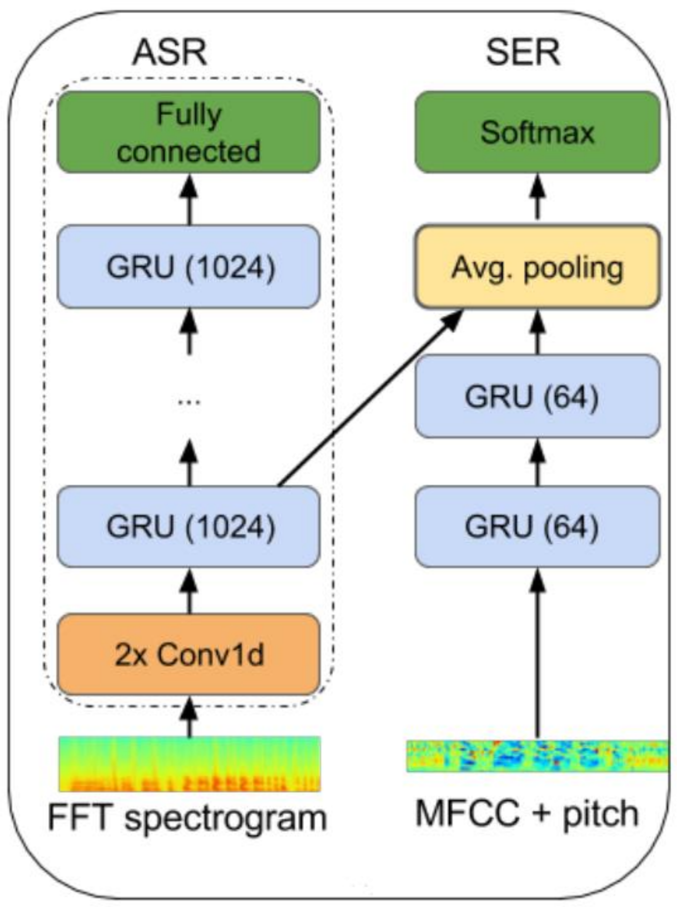


Key Takeaways from related work:

- Influence of linguistic knowledge in spoken utterances for SER task still remains unexplored.
- Selection of intermediate ASR layers needs to be studied thoroughly.

[2] https://www.aclweb.org/anthology/I17-1043.pdf

Proposed System

Representative features

Acoustic features : Mel-spectrogram

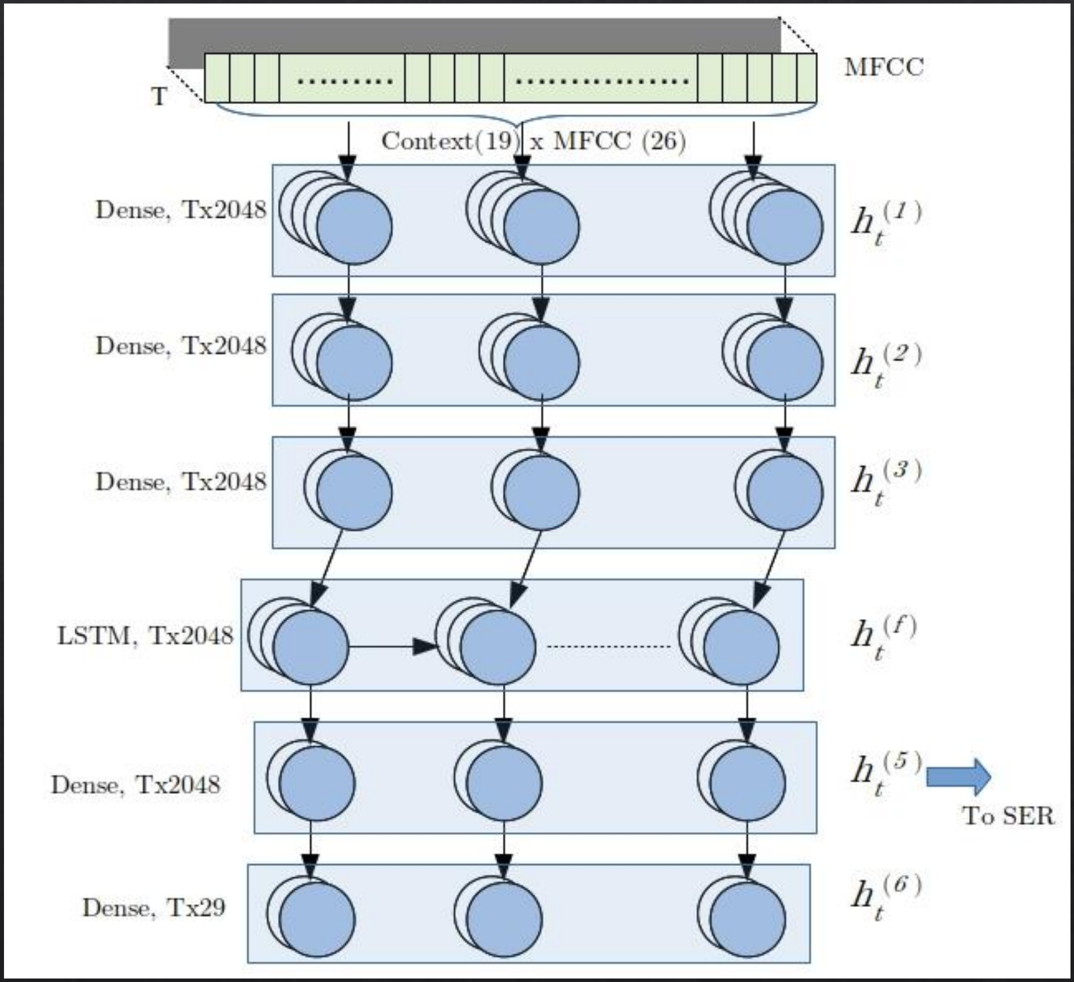
- Sampling rate = 16 kHz
- Frame duration = 25 msec
- Length of FFT window = 2048
- Hop length = 400 samples
- Number of bins on mel-scale = 128

Concatenate Δ and Δ- Δ for the mel-spectrogram.

Representative features

Deep encoded Linguistic features : DeepSpeech ASR [3]

- Note : Layers closer to output capture the linguistic content of speech while the layers close to input capture the acoustic content.[4]



DeepSpeech–1 architecture

[3] Mozilla, “DeepSpeech–0.4.0,”https://github.com/mozilla/DeepSpeech/releases, January 2019
[4] Swapnil B, Imran S, Sunil K, “End-to-End spoken language understanding: Bootstrapping in low resource scenarios,” Interspeech 2019.

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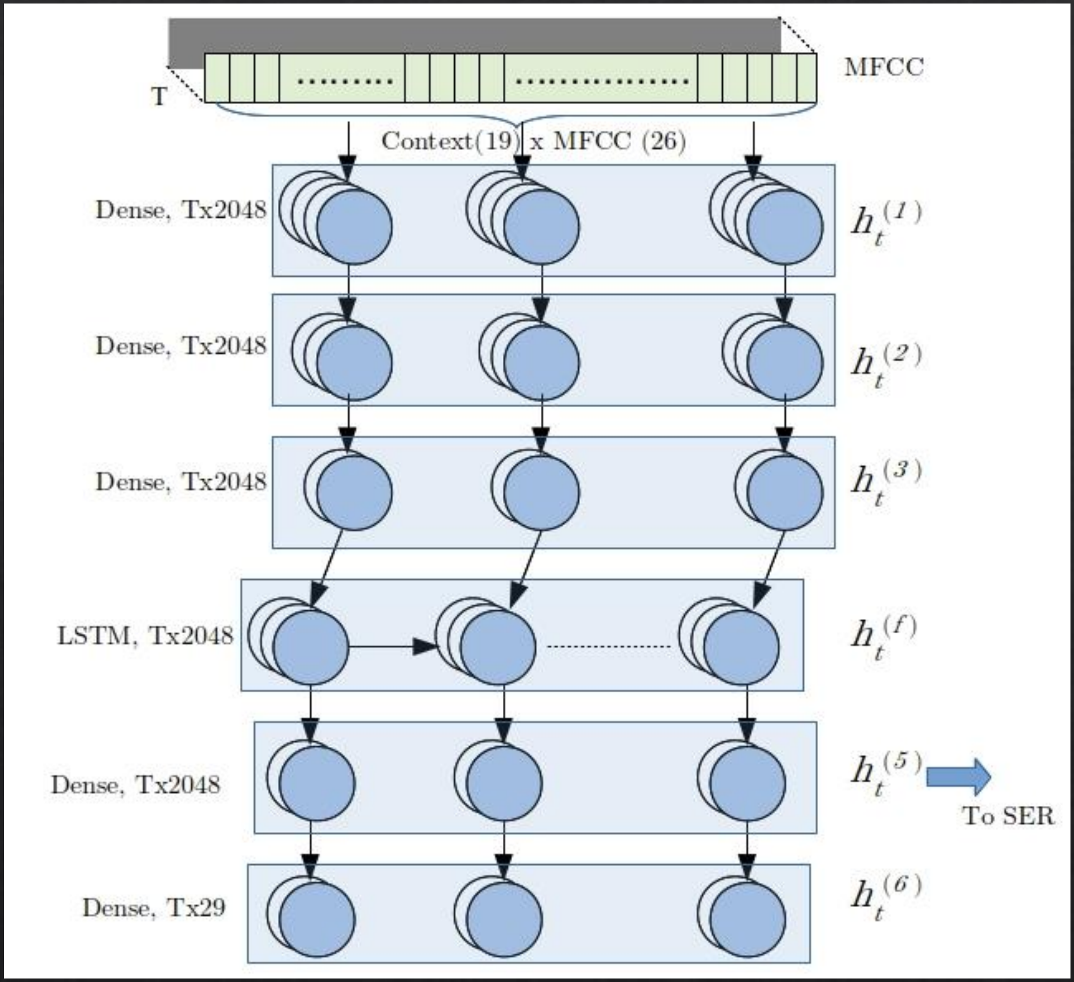
Can we get linguistic context of embedded emotion in the spoken utterance ?



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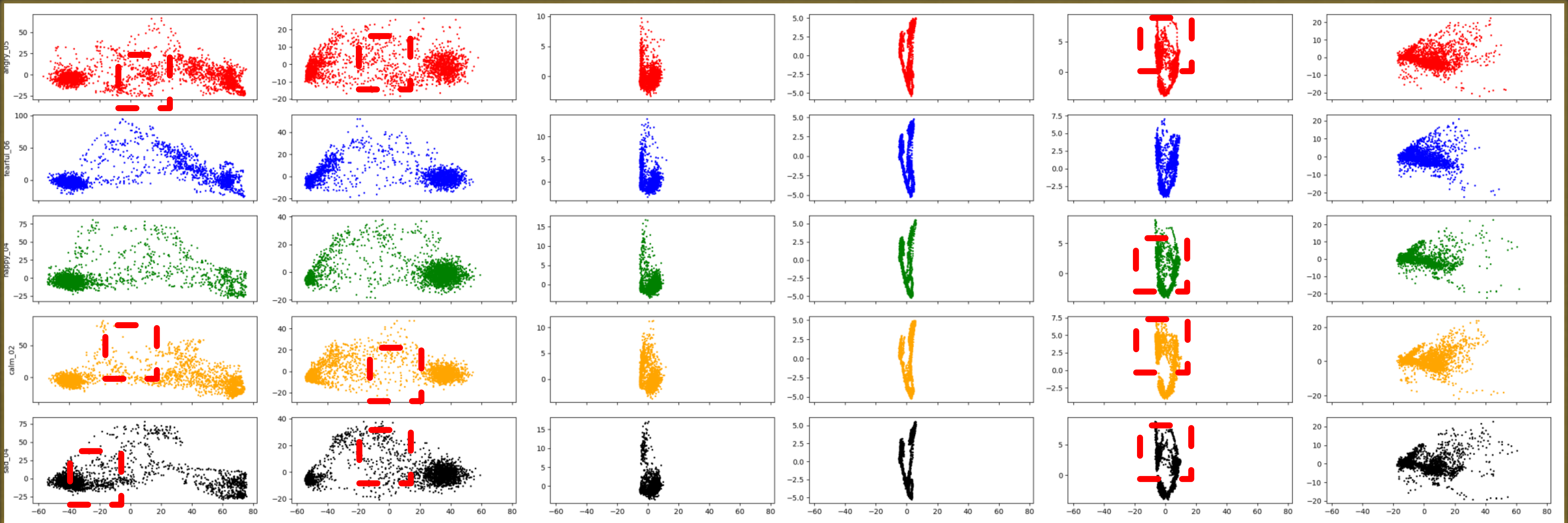


Visualization of activations from different layers of DeepSpeech model, for the same utterance spoken in different emotions. Columns represent the 6 layers and rows represent emotions. *anger*; *fearful*; *happy*; *calm*; *sad*

- 1st , 2nd and 5th layers show least correlation across the rows (emotions).
- Lesser correlation in 1st and 2nd layer is due to variations in speaker, gender etc.[4]
- We use the output from the 5th layer for getting the linguistic context for the SER task.

Proposed architecture

Encoder :

- 2 layers of 1-D convolutions.
  - ➢ Helps to learn temporal context between adjacent frames.

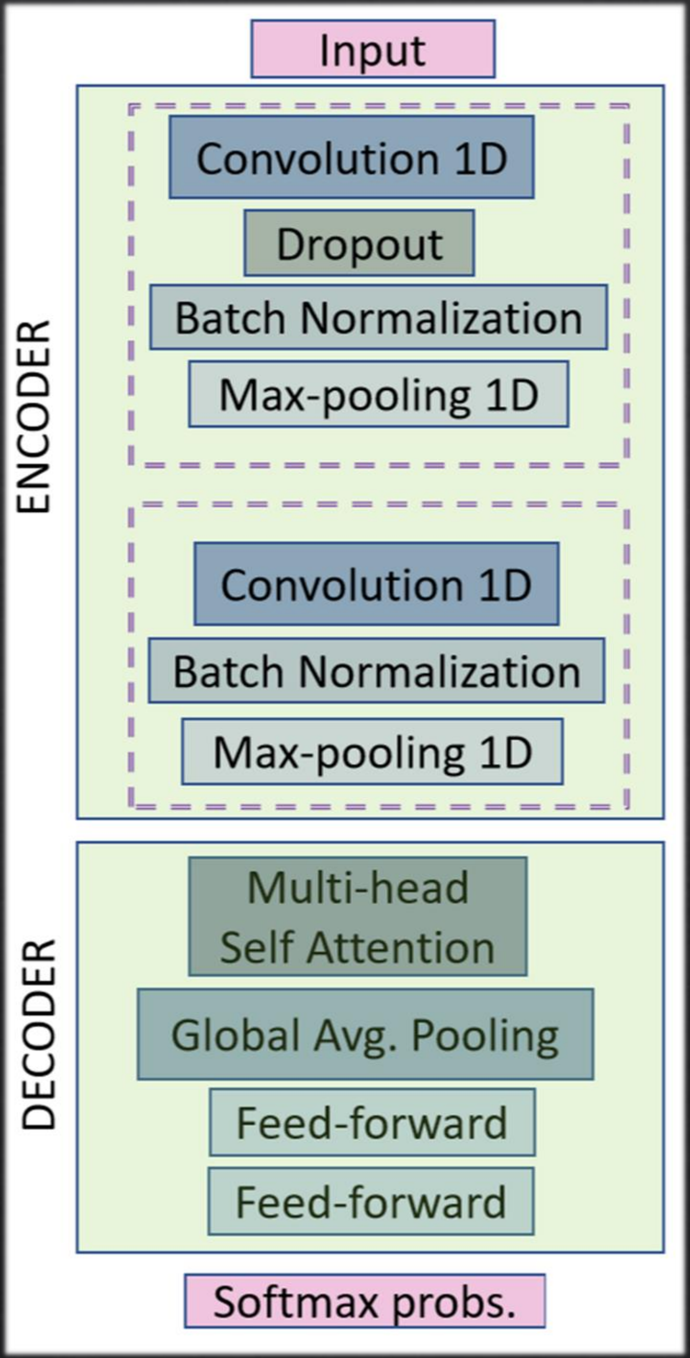
- 1-D convolution layer
  ➔ Batch normalization layer
  ➔ ReLU activation

Decoder :

- Multi-head self attention layer
  ➔ Average pooling
  ➔ 2 feedforward dense layers.

Output :

Softmax distribution over individual emotions.



Proposed Encoder – Decoder model architecture

Multi-head Self Attention

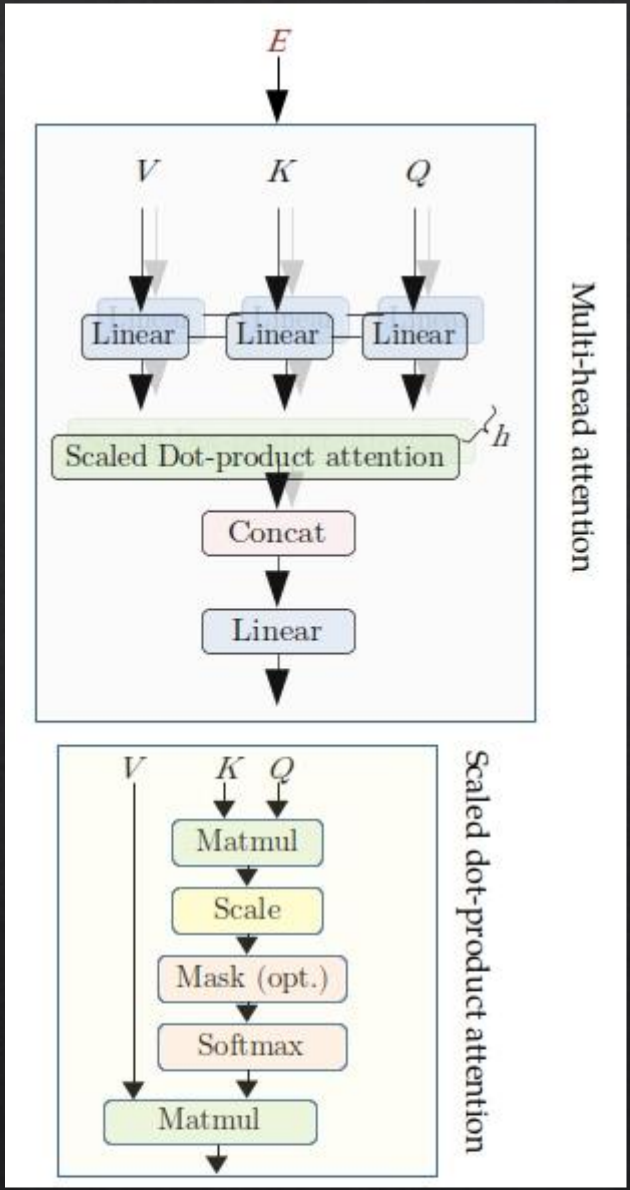
- Let E be the output of the encoder block
- W_i are trainable weight matrices
- d_i is the dimension
- A_i : Attention weight of a single head
- A_{MH} : Final multi-head self attention
- h : total number of heads

$$A_i = softmax\left(\frac{Q_i K_i^T}{\sqrt{d_K}}\right) V_i \ \forall i \in \{1,2, \ldots \text{h}\}$$

$$Q = EW_Q, \quad K = EW_K, \quad V = EW_V$$

$$A_{MH} = (A_1 \| A_2 \| \ldots \| A_h) W_E$$

$$\text{Context, } C = E + A_{MH}$$



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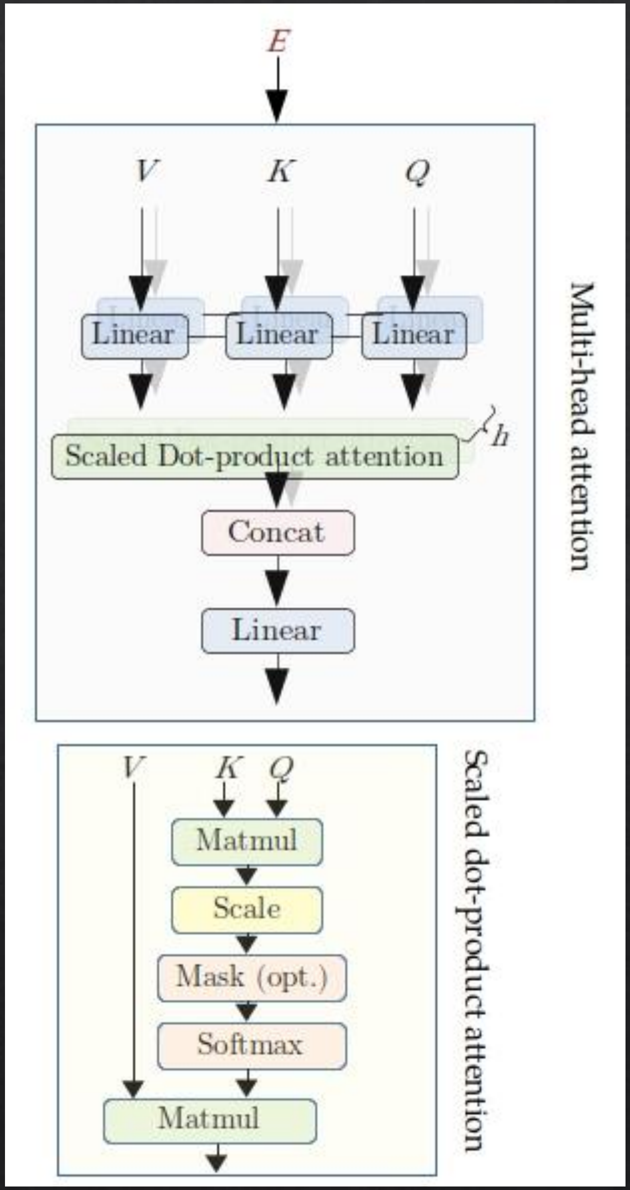
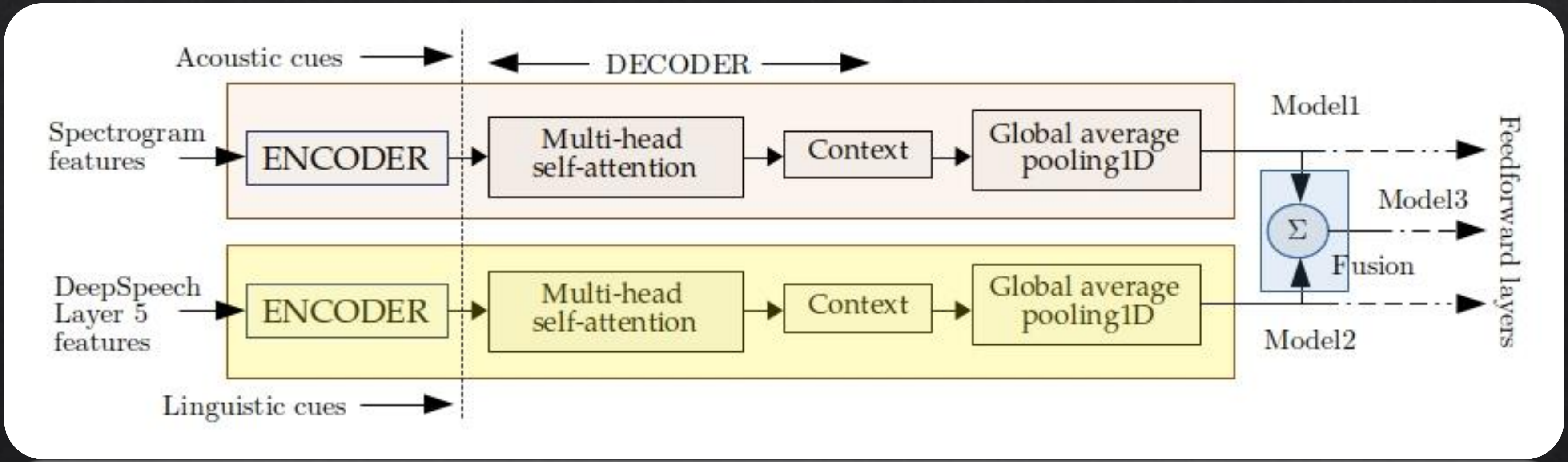
Var.	Dim.
E_i	[t X d_E]
Q_i	[t X d_Q]
K_i	[t X d_K]
$Q_i K_i^T$	[t X t]
V_i	[t X d_V]
$(Q_i K_i^T) V_i$	[t X d_V]



Experiments

- Dataset : IEMOCAP[5]
  - Recording setups : 2 { Improvised speech, scripted play }
  - Categorical Emotion classes : 4 { anger, happiness, neutral, sadness }

- Model configurations :



Model configurations : Model-1, Model-2, Model-3

[5] Carlos Busso, IEMOCAP: Interactive Emotional Dyadic Motion Capture database," Language resources and evaluation, 2008.

Results

Experiments with improvised recordings

Model (Input features)	Weighted Acc., WA	Unweighted Acc., UA
Yenigalla et al.,2018 [6] (only spectrogram)	71.3	61.6
Satt et al., 2017 [7]	68.8	59.4
Lee et al., 2015 [8]	63.8	62.85
Model - 1 (acoustic)	72.08	58.53
Model - 1 (downsampling + ensembling)	70.05	**63.27**
Model - 2 (linguistic)	69.56	54.62
Model - 3 (fusion)	**72.34**	58.31

Observation :

- Improvement using only Acoustic features ✓
- Improvement using Linguistic features (or +Acoustic features) ✗

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What if there is linguistic context embedded within the samples?

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What if the data itself has a combination of both scripted and improvised speech ?

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Experiments with scripted + improvised recordings

Model (Input features)	Weighted Accuracy, WA	Unweighted Accuracy, UA
Model - 1 (acoustic)	**70.82**	55.53
Model - 2 (linguistic)	62.03	51.96
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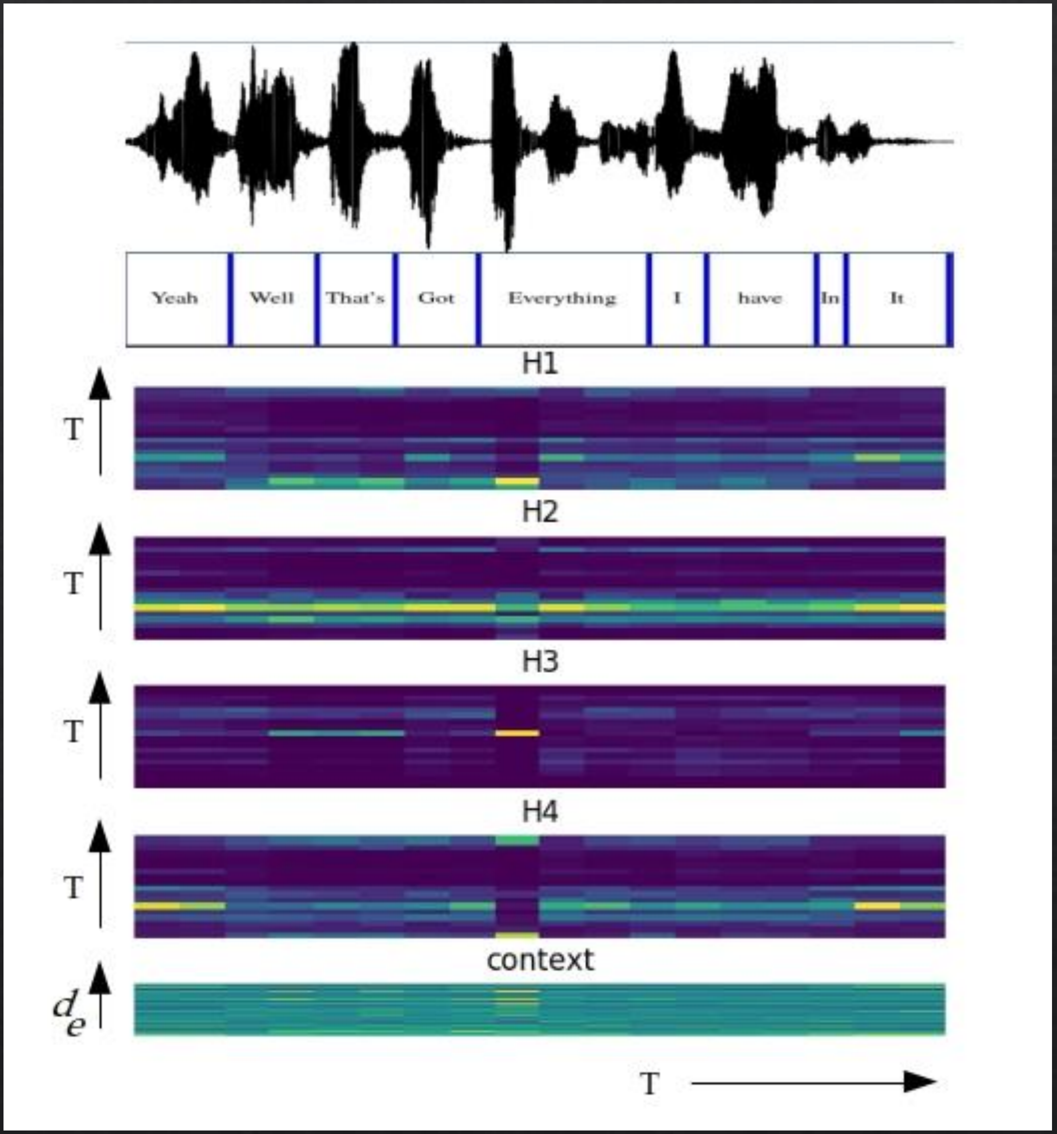
But, is the self-attention module actually helping?

Discussion

$$A_i = softmax\left(\frac{\boxed{Q_i K_i^T}}{\sqrt{d_K}}\right) V_i$$

- Model learns the acoustically significant frames and weighs them heavily during the formation of context.
- Strong emphasis around the word “everything” makes it almost distinctive as anger emotion.
- Not all heads contribute equally, most important and confident heads play a consistent role.



Attention weights (a T X T matrix) for each attention head.
T : timesteps, True emotion : *anger*

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- Less correlation of linguistic cues with the emotion than its acoustic counterpart in the improvised recordings.
- Combination of linguistic and acoustic features gives an improvement of
  - 6.29% for only scripted
  - 2.86% for combined scenario

  indicating usefulness of our approach.

Thank You !

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